Understanding inflation dynamics in the United States of America (USA): A univariate approach

THABANI NYONI

University of Zimbabwe, Department of Economics

19 February 2019

Understanding Inflation Dynamics in the United States of America (USA): A Univariate Approach

Nyoni, Thabani

Department of Economics

University of Zimbabwe

Harare, Zimbabwe

Email: nyonithabani35@gmail.com

ABSTRACT

This paper uses annual time series data on inflation rates in the USA from 1960 to 2016, to model and forecast inflation using the Box – Jenkins ARIMA technique. Diagnostic tests indicate that the US inflation series is I (1). The study presents the ARIMA (2, 1, 1) model for predicting inflation in the US. The diagnostic tests further show that the presented parsimonious model is stable and acceptable for predicting annual inflation rates in the US. The results of the study apparently show that inflation in the US is likely to be less than 2% over the out-of-sample forecast period (i.e 10 years). The study encourages policy makers to make use of tight monetary policy measures in order to maintain price stability in the US.

Key Words: Forecasting, Inflation, USA

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation has generally come in below central banks' targets in the advanced economies for several years now. Resource slack and commodity prices – as well as, for the United States, movements in the U. S dollar – appear to explain inflation's behaviour fairly well (Powell, 2018). Depending upon money demand and the velocity of money, inflation rates often diverge significantly in the short run from changes made by the Federal Reserve to the U. S money supply. The present situation is a perfect example: The demand for and velocity of money remain extremely low in the aftermath of the financial crisis and the deep recession. Consumer Price Index (CPI) has actually declined in 2009 for the first time in 60 years, despite a nearly double digit increase in the broad money supply. Excluding volatile food and energy prices, so-called core inflation measures have continued to decline this year and remain well within the Federal Reserve's informal target range of 1% - 2 %. Today's Federal Reserve Board possesses an important advantage over its predecessors in the 1970s and early 1980s – namely, real-time measures of inflation expectations provided by the Treasury Inflation-Protected Securities (TIPS) market. Should such expectations rise markedly in the years ahead, Fed policy makers will have less excuse than their predecessors if they do not act forcefully to keep inflation under control (Davis & Cleborne, 2010).

The Federal Open Market Committee (FOMC) is firmly committed to fulfilling its statutory mandate from the Congress of promoting maximum employment, stable prices, and moderate long term interest rates. The inflation rate in the long run is primarily determined by the monetary policy, and hence the Committee has the ability to specify a longer-run goal for inflation. In setting monetary policy, the Committee seeks to mitigate deviations of inflation from its longer-run goal. Measured on a 12-month basis, inflation has remained below the FOMC longer-run objective of 2% (Powell, 2018).

Inflation is the sustained increase in the general level of prices and services over time (Blanchard, 2000). The negative effects of inflation are widely recognized (Fenira, 2014). Inflation is one of the central terms in macroeconomics (Enke & Mehdiyev, 2014) as it harms the stability of the acquisition power of the national currency, affects economic growth because investment projects become riskier, distorts consuming and saving decisions, causes unequal income distribution and also results in difficulties in financial intervention (Hurtado *et al*, 2013). As the prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values (Mcnelis & Mcadam, 2004). To prevent the aforementioned undesirable outcomes of price instability, central banks require proper understanding of the future path of inflation to anchor expectations and ensure policy credibility; the key aspects of an effective monetary policy transmission mechanism (King, 2005). Inflation forecasts and projections are also often at the heart of economic policy decision-making, as is the case for monetary policy, which in most industrialized economies is mandated to maintain price stability over the medium term (Buelens, 2012). Economic agents, private and public alike; monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources (Hector & Valle, 2002). Decision-makers hence need to have a view of the likely future path of inflation when taking measures that are necessary to reach their objective (Buelens, 2012).

To avoid adjusting policy and models by not using an inflation rate prediction can result in imprecise investment and saving decisions, potentially leading to economic instability (Enke & Mehdiyev, 2014). The rate of price inflation in the United States of America has become both harder and easier to forecast, depending on one's point of view (Stock & Watson, 2007). In this study, we seek to model and forecast annual rates of inflation in the United States of America using simple and yet robust generalized univariate ARIMA models.

LITERATURE REVIEW

Meyler *et al* (1998) forecasted Irish inflation using ARIMA models with quarterly data ranging over the period 1976 to 1998 and illustrated some practical issues in ARIMA time series forecasting. Kock & Terasvirta (2013) forecasted Finnish consumer price inflation using Artificial Neural Network models with a data set ranging over the period March 1960 – December 2009 and established that direct forecasts are more accurate then their recursive counterparts. Kharimah *et al* (2015) analyzed the CPI in Malaysia using ARIMA models with a data set ranging over the period January 2009 to December 2013 and revealed that the ARIMA (1, 1, 0) was the best model to forecast CPI in Malaysia. Pincheira & Medel (2015) examined inflation with a data that spans from February 1999 to December 2011 and illustrated that the forecasting accuracy of the DESARIMA family models is high in stable-inflation countries, for which the RMSPE is around 100 basis points when a prediction is made 24 and even 36 months ahead. Nyoni (2018) studied inflation in Zimbabwe using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. Nyoni (2018), in yet another African study; modeled inflation in Kenya using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that can be used to forecast inflation in Kenya. Sarangi *et al* (2018) analyzed the consumer price index using Neural Network models with 159 data points and revealed that ANNs are better methods of forecasting CPI in India. Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; studied inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria.

MATERIALS & METHODS

Box – Jenkins ARIMA Models

One of the methods that are commonly used for forecasting time series data is the Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1976; Brocwell & Davis, 2002; Chatfield, 2004; Wei, 2006; Cryer & Chan, 2008). For the purpose of forecasting inflation rate in the USA, ARIMA models were specified and estimated. If the sequence $\Delta^d USA_t$ satisfies an ARMA (p, q) process; then the sequence of USA_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d USA_t = \sum_{i=1}^{p} \beta_i \Delta^d USA_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

which we can also re – write as:

$$\Delta^d USA_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i USA_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018).

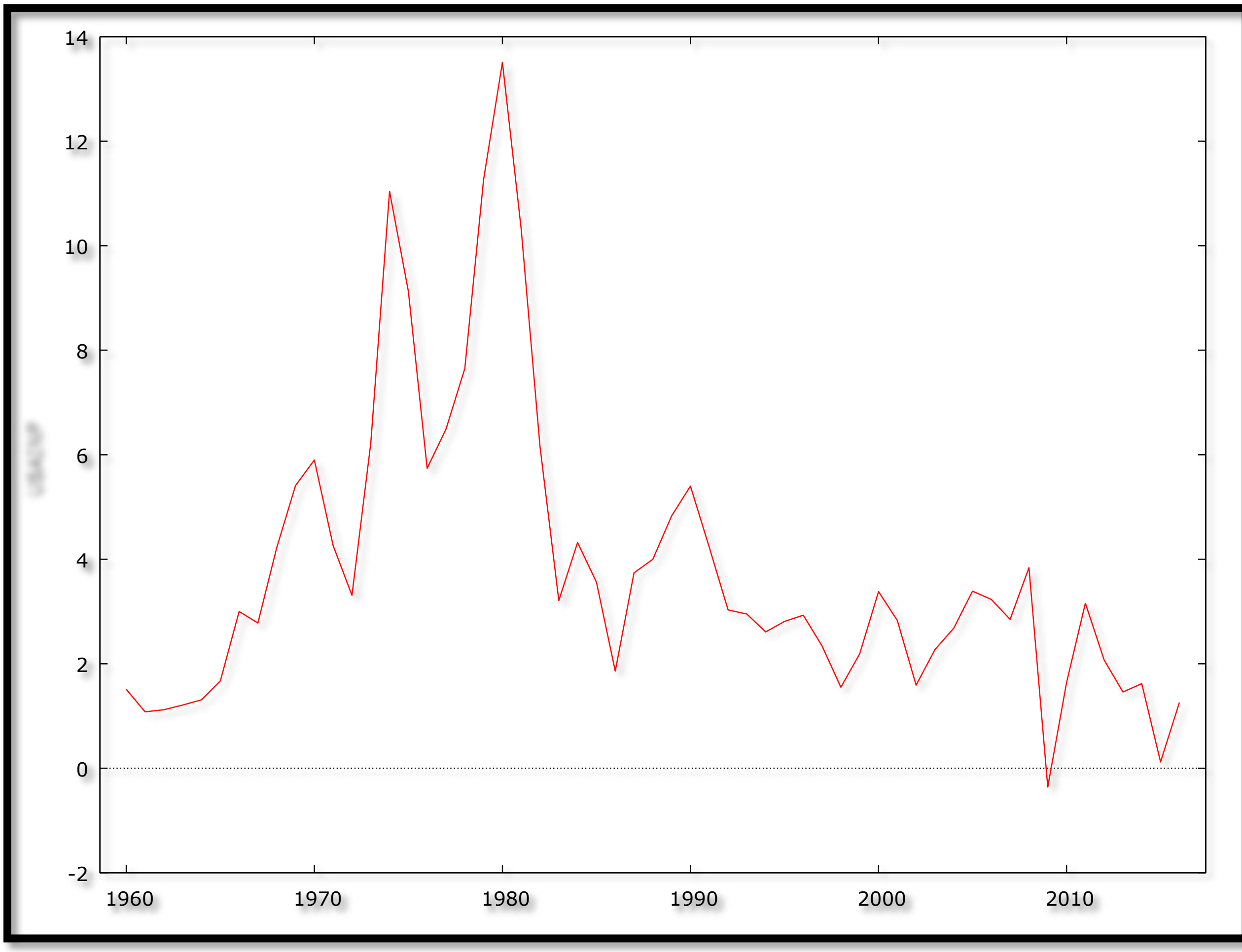
Data Collection

This study is based on a data set of annual rates of inflation in the USA (USAINF or simply USA) ranging over the period 1960 – 2016. All the data was taken from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Autocorrelation function for USAINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 1

LAG	ACF		PACF		Q-stat. [p-value]
1	0.8067	***	0.8067	***	39.0794 [0.000]
2	0.5511	***	-0.2853	**	57.6503 [0.000]
3	0.4334	***	0.2872	**	69.3492 [0.000]

4 0.4057 *** 0.0356 79.7943 [0.000]

5 0.4116 *** 0.1379 90.7520 [0.000]

6 0.3536 *** -0.1601 98.9945 [0.000]

7 0.2171 -0.1162 102.1632 [0.000]

8 0.0939 -0.0495 102.7686 [0.000]

9 0.0671 0.0973 103.0837 [0.000]

10 0.0882 -0.0260 103.6405 [0.000]

11 0.0457 -0.1451 103.7932 [0.000]

The ADF Test in Levels

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
USA	-1.997321	0.2872	-3.557472	@1%	Non-stationary
			-2.916566	@5%	Non-stationary
			-2.596116	@10%	Non-stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
USA	-3.383817	0.0641	-4.133838	@1%	Non-stationary
			-3.493692	@5%	Non-stationary
			-3.175693	@10%	Stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
USA	-1.010859	0.2766	-2.608490	@1%	Non-stationary
			-1.946996	@5%	Non-stationary
			-1.612934	@10%	Non-stationary

Figure 1 and tables 1 – 4 show that the USA series is non-stationary in levels.

The Correlogram (at 1st Differences)

Autocorrelation function for d_USAINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 5

LAG ACF PACF Q-stat. [p-value]

1 0.1486 0.1486 1.3041 [0.253]

2 -0.3584 *** -0.3890 *** 9.0291 [0.011]

3	-0.2510	*	-0.1437	12.8905 [0.005]
4	-0.0821		-0.1868	13.3118 [0.010]
5	0.2000		0.1140	15.8584 [0.007]
6	0.2126		0.0567	18.7933 [0.005]
7	-0.0720		-0.0535	19.1368 [0.008]
8	-0.1802		-0.0442	21.3337 [0.006]
9	-0.1320		-0.0975	22.5384 [0.007]
10	0.1897		0.1871	25.0785 [0.005]
11	0.1659		-0.0403	27.0653 [0.004]

ADF Test in 1st Differences

Table 6: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
USA	-7.063868	0.0000	-3.557472	@1%	Stationary
			-2.916566	@5%	Stationary
			-2.596116	@10%	Stationary

Table 7: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
USA	-7.103161	0.0000	-4.137279	@1%	Stationary
			-3.495295	@5%	Stationary
			-3.176618	@10%	Stationary

Table 8: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
USA	-7.133035	0.0000	-2.608490	@1%	Stationary
			-1.946996	@5%	Stationary
			-1.612934	@10%	Stationary

Tables 5 – 8 indicate that the USA series is an I (1) variable.

Evaluation of ARIMA models (without a constant)

Table 9

Model	AIC	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	218.4545	0.0042351	1.1831	1.6103	78.323
ARIMA (1, 1, 0)	220.7632	-0.00080657	1.2538	1.6758	75.758
ARIMA (0, 1, 1)	218.5827	0.004506	1.2081	1.6419	77.296
ARIMA (2, 1, 1)	**213.8552**	0.00087823	1.111	1.5148	77.555
ARIMA (1, 1, 2)	214.5636	0.0055535	1.1089	1.5248	76.476

ARIMA (2, 1, 2)	215.8494	-0.00039417	1.1178	1.5147	78.014
ARIMA (3, 1, 1)	215.8551	0.00085576	1.1112	1.5148	77.568
ARIMA (1, 1, 3)	216.3545	0.004892	1.1012	1.5218	75.427

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). The study will only consider the AIC as the criteria for choosing the best model for predicting inflation in the USA. Hence, the ARIMA (2, 1, 1) model is selected finally.

95% Confidence Ellipse & 95% 95% Marginal Intervals

Figure 2 [AR (1) & MA(1) components]

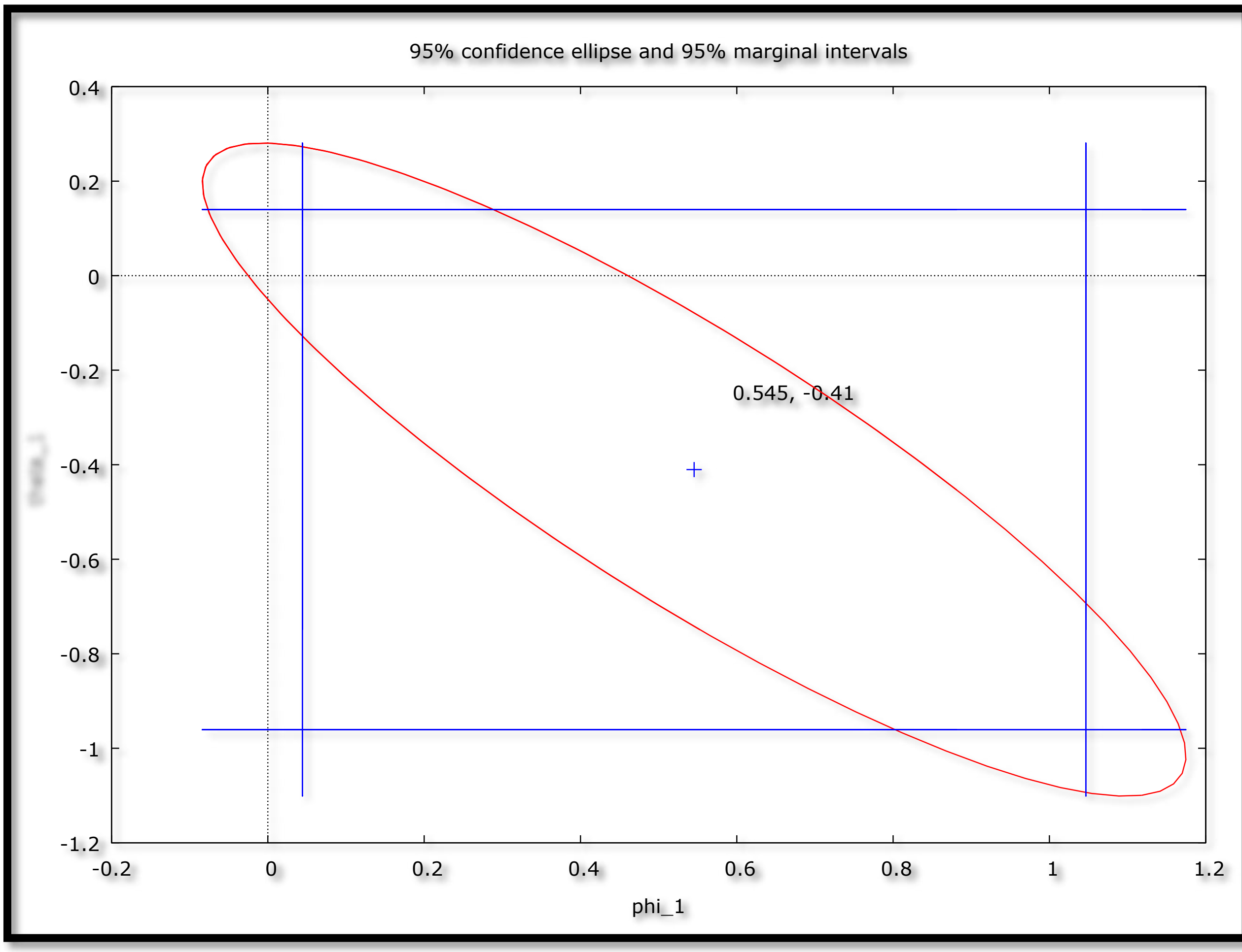


Figure 3 [AR (2) & MA (1) components]

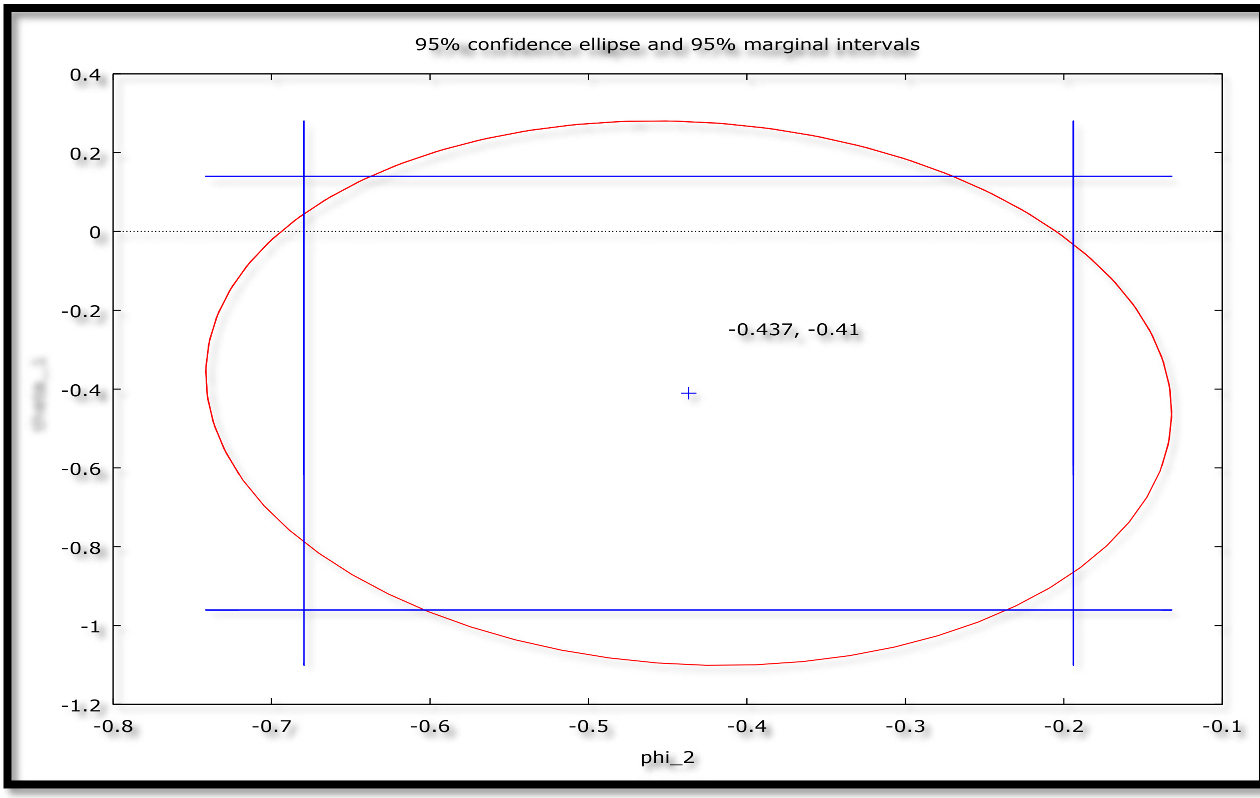
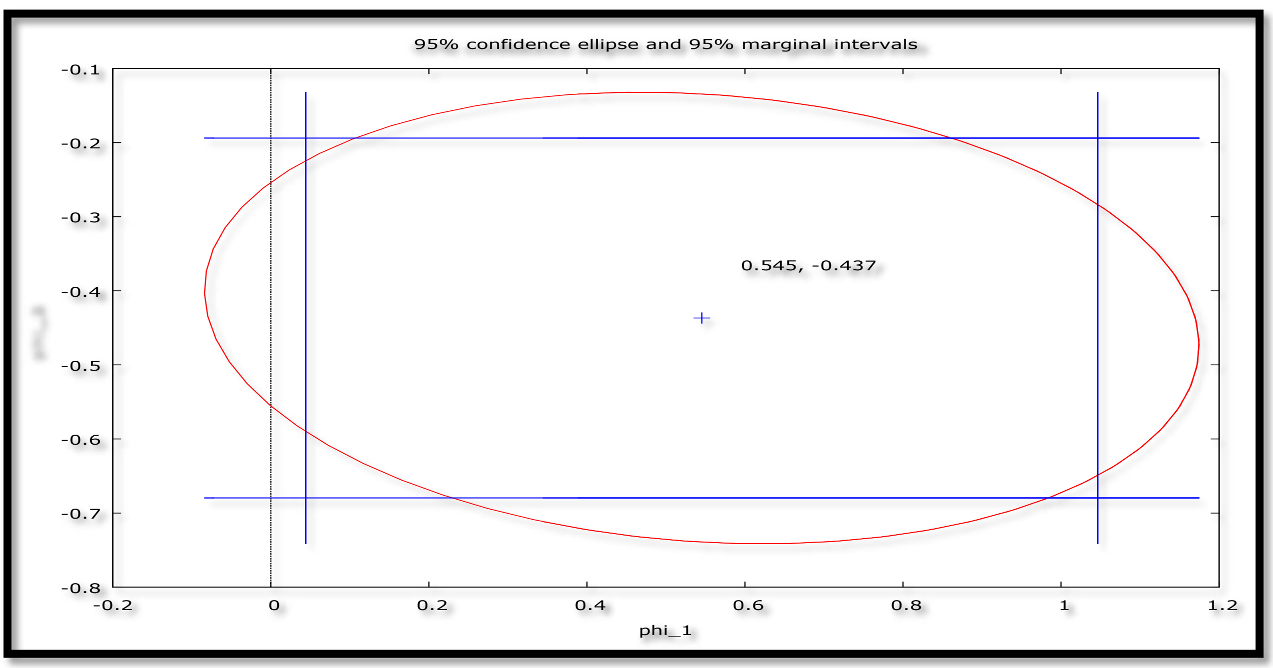


Figure 4 [AR (1) & AR (2) components]



Figures 2 – 4 demonstrate that the accuracy of our forecast as given by the ARIMA (2, 1, 1) model is satisfactory since it falls within the 95% confidence interval.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (2, 1, 1) Model

Table 10: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.096304	0.0000	-3.560019	@1%	Stationary
			-2.917650	@5%	Stationary
			-2.596689	@10%	Stationary

Table 11: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.234946	0.0000	-4.140858	@1%	Stationary
			-3.496960	@5%	Stationary
			-3.177579	@10%	Stationary

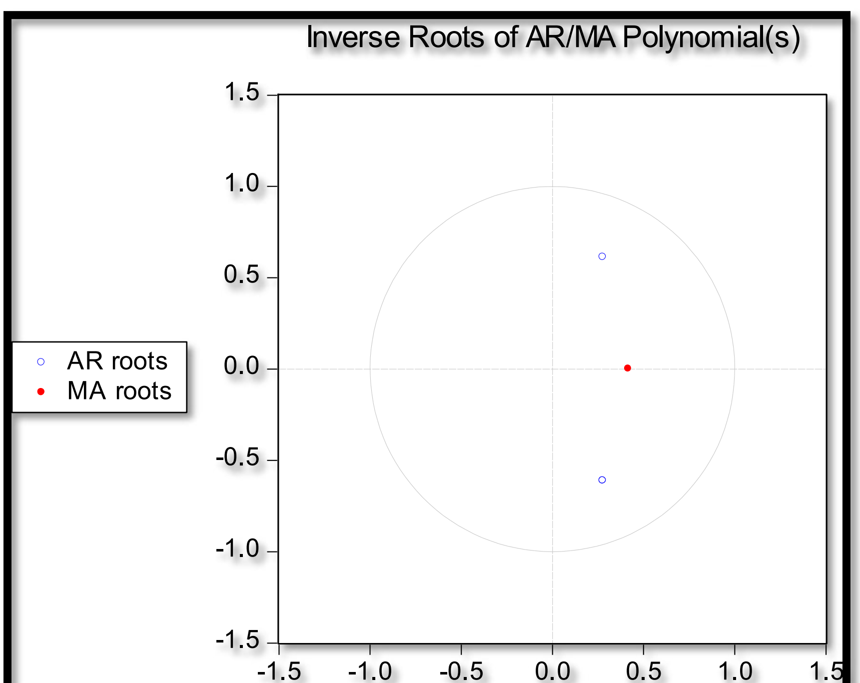
Table 12: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.166405	0.0000	-2.609324	@1%	Stationary
			-1.947119	@5%	Stationary
			-1.612867	@10%	Stationary

Tables 10, 11 and 12 show that the residuals of the ARIMA (2, 1, 1) model are stationary and hence the ARIMA (2, 1, 1) model is suitable for forecasting inflation in the USA.

Stability Test of the ARIMA (2, 1, 1) Model

Figure 5



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (2, 1, 1) model is stable and suitable for predicting inflation in the USA over the period under study.

FINDINGS

Descriptive Statistics

Table 13

Description	Statistic
Mean	3.8053
Median	3.03
Minimum	-0.36
Maximum	13.51
Standard deviation	2.8233
Skewness	1.5551
Excess kurtosis	2.3337

As shown above, the mean is positive, i.e. 3.8053%. The minimum is -0.36% and the maximum is 13.51%. The skewness is 1.5551 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis was found to be 2.3337; implying that the inflation series is not normally distributed.

Results Presentation[1]

Table 14

ARIMA (2, 1, 1) Model:

$$\Delta USA_{t-1} = 0.54542\Delta USA_{t-1} - 0.436741\Delta USA_{t-2} - 0.4103\mu_{t-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots [3]$$

P: (0.0291) (0.0003) (0.1349)

S. E: (0.2499) (0.1210) (0.2744)

Variable	Coefficient	Standard Error	z	p-value
AR (1)	0.54542	0.249895	2.183	0.0291**
AR (2)	-0.436741	0.12103	-3.609	0.0003***
MA (1)	-0.4103	0.274404	-1.495	0.1349

Predicted Annual Inflation in the USA

Table 15

Year	Prediction	Std. Error	95% Confidence Interval
2017	2.01	1.515	-0.96 - 4.98

[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*

2018	1.92	2.291	-2.57 -	6.41
2019	1.55	2.572	-3.50 -	6.59
2020	1.38	2.688	-3.89 -	6.65
2021	1.45	2.807	-4.05 -	6.95
2022	1.57	2.977	-4.27 -	7.40
2023	1.60	3.168	-4.61 -	7.80
2024	1.56	3.337	-4.98 -	8.10
2025	1.53	3.482	-5.29 -	8.36
2026	1.53	3.616	-5.56 -	8.62

Table 15 (with a forecast range from 2017 – 2026), clearly show that annual inflation rates in the USA are generally projected to be below 2% over the next decade. The most important part of these results is that they are consistent with the FOMC's longer-run objective of 1 – 2% inflation. US policy makers are envisaged to benefit from our forecasts in terms of deriving prudent policy actions and using the forecasts in their short to mid-term plans.

CONCLUSION

The economic and statistical models and relationships used to help produce economic forecasts are necessarily imperfect descriptions of the real world, and the future path of the economy can be affected by myriad unforeseen developments and events (Powell, 2018). Policy makers ought to pay attention to the risk of adjustment in economic operation and maintain the stability and continuity of microeconomic regulation and control in order to prevent the economy form severe fluctuations and adjust the corresponding target value according to the actual situation (Wabomba *et al*, 2016). We applied the Box-Jenkins ARIMA technique to examine inflation in the US over the period 1960 to 2016. Our aim was to forecast inflation rate for the upcoming period from 2017 to 2026. The ARIMA (2, 1, 1) model was found to be the most parsimonious model. In general our forecasts are in line with the FOMC's projections and this shows that indeed our predictions are in the right direction as already shown by the forecast evaluation statistics in table 9 above and also supported by diagnostic tests in tables 10 – 12 and figures 2 – 5 above. Based on the results, policy makers in the US should engage more proper economic policies in order to maintain price stability and hence foster sustainable economic growth. In this regard, the Federal Reserve System is encouraged to prioritize tight monetary policy measures in order to maintain price stability in the US.

REFERENCES

[1] Blanchard, O (2000). Macroeconomics, 2nd Edition, *Prentice Hall*, New York.

[2] Box, G. E. P & Jenkins, G. M (1976). Time Series Analysis: Forecasting and Control, *Holden Day*, San Francisco.

[3] Brocwell, P. J & Davis, R. A (2002). Introduction to Time Series and Forecasting, *Springer*, New York.

[4] Buelens, C (2012). Inflation modeling and the crisis: assessing the impact on the performance of different forecasting models and methods, *European Commission*, Economic Paper No. 451.

[5] Chatfield, C (2004). The Analysis of Time Series: An Introduction, 6th Edition, *Chapman & Hall*, New York.

[6] Cryer, J. D & Chan, K. S (2008). Time Series Analysis with Application in R, *Springer*, New York.

[7] Davis, J. H & Cleborne, J (2010). Recent policy actions and the outlook for US inflation, *Vanguard Investment Counseling and Research*.

[8] Enke, D & Mehdiyev, N (2014). A Hybrid Neuro-Fuzzy Model to Forecast Inflation, *Procedia Computer Science*, 36 (2014): 254 – 260.

[9] Fenira, M (2014). Democracy: a determinant factor in reducing inflation, *International Journal of Economics and Financial Issues*, 4 (2): 363 – 375.

[10] Hector, A & Valle, S (2002). Inflation forecasts with ARIMA and Vector Autoregressive models in Guatemala, *Economic Research Department*, Banco de Guatemala.

[11] Hurtado, C., Luis, J., Fregoso, C & Hector, J (2013). Forecasting Mexican Inflation Using Neural Networks, *International Conference on Electronics, Communications and Computing*, 2013: 32 – 35.

[12] Kharimah, F., Usman, M., Elfaki, W & Elfaki, F. A. M (2015). Time Series Modelling and Forecasting of the Consumer Price Bandar Lampung, *Sci. Int (Lahore).*, 27 (5): 4119 – 4624.

[13] King, M (2005). Monetary Policy: Practice Ahead of Theory, *Bank of England*.

[14] Kock, A. B & Terasvirta, T (2013). Forecasting the Finnish Consumer Price Inflation using Artificial Network Models and Three Automated Model Section Techniques, *Finnish Economic Papers*, 26 (1): 13 – 24.

[15] Mcnelis, P. D & Mcadam, P (2004). Forecasting Inflation with Think Models and Neural Networks, *Working Paper Series*, European Central Bank.

[16] Meyler, A., Kenny, G & Quinn, T (1998). Forecasting Irish Inflation using ARIMA models, *Research and Publications Department*, Central Bank of Ireland.

[17] Nyoni, T & Nathaniel, S. P (2019). Modeling Rates of Inflation in Nigeria: An Application of ARMA, ARIMA and GARCH models, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 91351.

[18] Nyoni, T (2018). Modeling and Forecasting Inflation in Zimbabwe: a Generalized Autoregressive Conditionally Heteroskedastic (GARCH) approach, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88132.

[19] Nyoni, T (2018). Modeling and Forecasting Naira / USD Exchange Rate in Nigeria: a Box – Jenkins ARIMA approach, *University of Munich Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88622.

[20] Nyoni, T (2018). Modeling and Forecasting Inflation in Kenya: Recent Insights from ARIMA and GARCH analysis, *Dimorian Review*, 5 (6): 16 – 40.

[21] Nyoni, T. (2018). Box – Jenkins ARIMA Approach to Predicting net FDI inflows in Zimbabwe, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 87737.

[22] Pincheira, P. M & Medel, C. H (2015). Forecasting inflation with a Simple and Accurate Benchmark: The case of the US and a set of inflation targeting countries, *Journal of Economics and Finance*, 65 (1): 1 – 28.

[23] Powell, J. H (2018). Monetary Policy Report, *Board of Governors of the Federal Reserve System*, Federal Reserve System.

[24] Sarangi, P. K., Sinha, D., Sinha, S & Sharma, M (2018). Forecasting Consumer Price Index using Neural Networks models, *Innovative Practices in Operations Management and Information Technology* – Apeejay School of Management, pp: 84 – 93.

[25] Stock, H & Watson. M. W (2007). Why has US inflation become harder to forecast? *Journal of Money, Credit and Banking*, 39 (1): 1 – 31.

[26] Wabomba, M. S., Mutwiri, M. P & Mungai, F (2016). Modeling and forecasting Kenyan GDP using Autoregressive Integrated Moving Average (ARIMA) models, *Science Publishing Group – Science Journal of Applied Mathematics and Statistics*, 4 (2): 64 – 73.

[27] Wei, W. S (2006). Time Series Analysis: Univariate and Multivariate Methods, 2nd Edition, *Pearson Education Inc*, Canada.